Gender and Banking: Are Women Better Loan Officers?

Thorsten Beck[•]
CentER, Dept. of Economics, Tilburg University and CEPR

Patrick Behr[#]
EBAPE, Fundacao Getulio Vargas

Andre Guettler[*]
EBS Business School

Abstract

Using a unique data set for a commercial bank in Albania, we analyze gender differences in loan officer performance. Loans screened and monitored by female loan officers have a lower likelihood to turn problematic than loans handled by male loan officers. This effect cannot be explained by borrower or loan officer selection or differences in screening, work load and experience. However, while the performance gap always exists for female borrowers, female loan officers only gain a performance advantage with male borrowers with experience and do not have an advantage with borrowers that are legal entities. We therefore interpret this as suggestive evidence for female loan officers' better capacity to build trust relationships with borrowers.

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[•]Department of Economics and European Banking Center, Tilburg University, and CEPR.
[#]Brazilian School of Public and Business Administration (EBAPE), Getulio Vargas Foundation (FGV).
*Department of Finance, Accounting, and Real Estate, EBS Business School.

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1. Introduction

Does gender matter in banking? We use a unique loan-level data set for a commercial bank in Albania over the period 1996 to 2006 to assess the relationship between borrowers' and loan officers' gender and loan performance. Specifically, we investigate whether male or female loan officers experience a lower arrear probability on "their" loans.

The recent banking literature has pointed out that incentives of loan officers can have strong effects on lending outcomes. For instance, Agarwal and Wang (2009) show that the choice of effort made by loan officers depends on the compensation scheme implemented by the bank, the information asymmetry between the loan officer and the bank, and the loan officer's career concerns. Hertzberg et al. (2010) show that loan officers are more likely to reveal negative information in the case of job rotation because it seems to be better if the loan officer reveals this kind of negative information herself instead of having bad information being revealed by a successor loan officer. None of these papers, however, has explicitly focused on gender differences.

The recent finance literature has pointed out that risk aversion, overconfidence and mutual trust, dimensions across which men and women are found to differ, impact financial decision making and performance. For instance, several studies have shown that women seem to be more risk averse than men (e.g. Sunden and Surette, 1998; Agnew et al., 2003).[1] Others argue that men are more overconfident than women (e.g. Barber and Odean, 2001; Niederle and Vesterlund, 2007). One may hypothesize that such differences should also be reflected in the

[1] Croson and Gneezy (2009) provide an excellent overview over the literature on differences in risk aversion between women and men and other reasons for gender differences.

relative performance of male and female loan officers. For instance, a higher degree of risk aversion of female loan officers may result in loans handled by female loan officers being less likely to be in arrears because women grant loans more restrictively. Along the same lines, higher overconfidence of male loan officers could result in male loan officers screening and monitoring too many loans, eventually leading to an inferior performance compared to female loan officers. Another competing hypothesis is that loan officers might have an easier time building a trust relationship and exploiting monitoring opportunities with borrowers of their own gender, hence, we would expect to find a lower arrear probability of female borrowers if the loan is approved and monitored by a female rather than by a male loan officer, with the reverse holding for male borrowers.

While gender-dependent loan officer performance has not been explored so far[2], gender differences have been analyzed in a variety of other fields in financial economics, such as investment decisions, equity analyst performance, corporate financial decisions, corporate boards and mutual fund management. The evidence on performance and behavioral differences between women and men is mixed in this literature. Barber and Odean (2001) find evidence that female investors seem to be less overconfident and, thus, trade less frequently. This leads to a superior

[2] Two recent studies explore whether female borrowers are treated differently by lenders (Alesina et al., 2012; Bellucci et al., 2010). The key differences between these two studies and ours are that we investigate performance differences associated with loan officer gender and that our data allow for the exact matching between borrowers and loan officers. Furthermore, we also have access to loan application data, which enables us to investigate differences in borrower selection across loan officer gender. See also Wilson et al. (2007) who explore loan officers' perceptions of female and male business owners.

performance of female investors. Levi et al. (2010) show that in the case of female CEOs, the bid premium over the pre-announcement target share price is much smaller than compared to M&A deals with male counterparts. Kumar (2010) finds that female stock analysts issue more accurate forecasts.[3] Huang and Kisgen (2009) find that acquisitions made by female CFO firms have significantly higher announcement returns and argue that women appear to undertake greater scrutiny and exhibit less hubris in acquisition decisions. Additionally, female CFOs issue debt less frequently, and debt and equity issuances are associated with higher announcement returns. There is also evidence for close cooperation between female directors and executives if both are in a minority position (Matsa and Miller, 2011). Finally, Adams and Ferreira (2009) show that female directors have a significant impact on board inputs and firm outcomes. In particular, female directors are more likely to join monitoring committees, which seems to strengthen monitoring.[4]

This paper tests the hypothesis that female and male loan officers perform differently, which is important for researchers and practitioners alike. First, it adds to the existing literature on differences between women and men in financial decision making, helping to shed more light on whether and along which dimensions female and male decision makers differ. Second, our results also shed light on gender differences in loan officer performance, with repercussions for

[3] On the other hand, Green et al. (2009) analyze the performance of male versus female Wall Street equity analysts and document that male analysts seem to have better forecasting abilities, i.e. women seem to perform worse at hard, quantifiable tasks.

[4] Ahern and Dittmar (2012), however, show that a substantial increase in female board participation due to a political mandate can have negative repercussions for firm performance.

the organization of borrower screening and monitoring processes.

For our analyses, we use a unique loan-level data set including more than 31,000 loan applications provided by a commercial bank in Albania serving individual borrowers, small and medium-sized enterprises and microenterprises. For each loan, we can identify the loan officer who screened the borrower and subsequently monitored her over the lifetime of the loan. If a borrower experiences payment difficulties, this can thus be directly linked to a specific loan officer. The data set also includes extensive information about borrower characteristics such as the gender or the marital status of the borrower but also asset size, profits and leverage of her enterprise, information about loan characteristics such as size, maturity and interest rate of the loan, and loan officer characteristics such as gender and experience within the institution. One particularly advantageous feature of our data set is that it comprises information on rejected applicants, which enables us to explicitly test for sample selection and screening differences between female and male loan officers. Crucially, we show that the assignment of applicants to loan officers is independent of the gender of the applicant or the gender of the loan officer. This random component in the data allows us to formally test and rule out that the borrower pools are different across loan officer gender. To test the robustness of our findings and to demonstrate that our results hold beyond the case of Albania, we run the analyses using a data set from the same bank holding company for Bolivia.

We find that loans screened and monitored by female loan officers turn significantly less often problematic, that is, they are significantly less often in arrears for more than 30 days than if screened and monitored by male loan officers. This result holds for both female and male borrowers and is robust to controlling for the borrower's gender and for the correlation between the borrower's and loan officer's gender. Besides the statistical significance, the performance advantage of female loan officers is also economically significant, as in our baseline analysis female loan officers have arrear probabilities for female and male borrowers which are 4 to 5 percentage points lower than the arrear probabilities of male loan officers. Our results are robust to different sample cuts and alternative performance measures. These findings suggest that not only the institutional and governance structure of financial institutions matters, but also the gender of the people operating in a given bank structure.[5] Finding a performance gap across gender of loan officers is a novel result in the literature.

We also explore possible explanations for this performance advantage of female loan officers. First, we cannot find any difference between female and male loan officers in their acceptance of applicants. Female loan officers do not grant loans more restrictively compared with male loan officers once we control for observable applicant characteristics. Furthermore, we find that female loan officers screen loan applications in the same way as male loan officers after accounting for unobservable applicant characteristics. Specifically, rejected applicants are equally likely to be accepted by male loan officers than by female loan officers in a further loan request if screened by a loan officer of a different gender. Second, we do not detect any differences in the workload of male vis-à-vis female loan officers. If male loan officers had a significantly higher workload, this might be an indication of a higher degree of overconfidence of male loan officers. Given our results, this does not seem to be the case. Third, our results do not vary with different experience levels of female and male loan officers in the case of female borrowers.[6]

[5] See also Berger et al. (2005) and Liberti and Mian (2008) on the importance of financial institutions' design.

[6] Experience might be negatively related to loan risk if loan officers gain expertise on screening and monitoring borrowers over time. Experimental evidence supports this argument. Andersson (2004) investigates the role of

However, we find that female loan officers are not always better than their male colleagues, but only under specific conditions, which provide insights into the reason for their performance advantage. First, female loan officers always have a performance advantage over male loan officers with female borrowers, independent of experience, while they gain a performance advantage with male borrowers only with experience. Second, there is no performance difference associated with loan officer gender for loans to legal entities (i.e. any entity other than a person, such as a partnership or corporation). More specifically, loans to legal entities are as likely to have repayment difficulties if screened and monitored by female loan officers as if screened and monitored by male loan officers.

These findings provide suggestive evidence for the hypothesis that women are better at building trust relationships and exploit monitoring possibilities. This explanation is in line with experimental evidence by Eckel and Grossman (2001) who conclude that women are more likely to reach agreements with women, compared to other combinations.[7] It also relates directly to the findings of Adams and Ferreira (2009) who find results suggesting that the presence of women on corporate boards strengthens monitoring.

While novel results, our findings are subject to an important caveat. The ideal way to establish a causal effect of gender on loan officer performance would be through a randomized experiment. Such randomization would have to take place along two dimensions: on the decision

experience in lending and shows that more experienced participants search for significantly more clues in the data than inexperienced participants.

[7] On the other hand, Bagues and Esteve-Volart (2010) find that the presence of female evaluators negatively affects the chance of a female job candidate to be hired.

to become loan officer and the assignment of applicants to loan officers. While the latter is certainly feasible, the former seems impossible to undertake in the real world as one cannot randomly choose individuals from the overall population to work as loan officers for a bank. In our analysis, we try to establish that our findings are not biased due to the non-experimental nature of the data. Unlike in a randomized experiment, however, we are left with the possibility that the performance gap between male and female loan officers is driven by unobservable borrower characteristics that female loan officers are better in distinguishing. In addition, we cannot exclude the possibility that female loan officers differ from their male colleagues along time-variant dimensions that we are not able to capture, although we discuss in depth why it is unlikely that such differences would drive our results.

The remainder of the paper is organized as follows. Section 2 discusses the institutional background and the data and section 3 the methodology. Section 4 presents our main results and several robustness checks. Section 5 explores possible explanations for the performance differences between female and male loan officers. We conclude in section 6.

2. Data

2.1 INSTITUTIONAL BACKGROUND

We use a unique loan level data set from a commercial lender serving microenterprises and small- and medium-sized enterprises (SMEs) in Albania to analyze gender-related loan officer performance differences. We obtain all rejected and accepted loan applications by the lender over the period January 1996 to December 2006 from four branches of the bank in the Albanian capital, Tirana. The lender is part of an international banking group operating in more than a dozen countries worldwide. Business, housing improvement, and consumption loans for small and micro entrepreneurs are the dominant loan types in our dataset. To be able to investigate performance differences associated with loan officer gender our data set also contains information on 203 loan officers.

With regard to performance and cost structure, our lender can be compared to small U.S. or European commercial banks serving SMEs, both in terms of its financial structure as well as in average loan size, adjusted for GNI per capita.[8] Hence, while our lender operates in a developing country, it does standard banking business that is comparable to the business of small commercial banks serving SMEs in the U.S. or Europe.

In analyzing performance differences between female and male loan officers, we focus on the arrear probability of a loan. Specifically, we explore whether loans screened and monitored by female loan officers are associated with a different arrear probability than loans screened and monitored by male loan officers. Critically, loans are screened and monitored by the same loan

[8] The pre-tax return on equity (RoE) of the lender averaged 17.4 percent over the time period 1997 to 2006. The average pre-tax RoE of U.S. commercial banks with less than 1 billion U.S. dollars (USD) in assets included in Bankscope averaged 15 percent over a similar time period (1995-2004), the respective pre-tax RoE for European commercial banks with assets below 1 billion USD included in Bankscope was 11.6 percent. The lender's cost-income ratio (CIR) over the years 2006 to 2008 averaged 71.4 percent, while the CIR of the mentioned U.S. banks averaged 73.2 percent between 1995 and 2004, and the CIR of the European banks averaged 80 percent. The lender is also comparable to U.S. banks with regard to the average loan size granted. For instance, in 2006 the lender's average loan size was 3,321 USD. If we standardize this figure with the ratio of the Albanian to the U.S. gross national income (GNI) per capita for that year, we get an average loan size of approximately 21,300 USD. This compares to an average loan size of 28,000 USD for SMEs in the U.S. as reported by the U.S. Small Business Association per end of June 2007.

officer and arrears are recorded automatically so that the reported arrears cannot be influenced by the loan officer. We define arrear probability as the probability that a loan is in arrears for more than 30 days at any time over the whole lifetime of the loan. We focus on the 30 day threshold because if a loan is in arrears for more than 30 days, the lender automatically increases the monitoring intensity, for instance, by calling the borrower in order to learn about the reasons for the payment delay. Hence, loans in arrears for more than 30 days are seen as problem loans and are subject to a particular treatment, which is associated with additional (monitoring) costs. This, in turn, should result in a lower profitability of the bank and may therefore be used as a performance indicator.[9]

The second reason why we focus on arrear probability as a performance indicator is that during the sample period the lender used an incentive scheme based on the arrear probability as defined in this study. If a loan officer had fewer loans in arrears for more than 30 days, this would increase the loan officer's salary payment. According to the lender, there are no systematic differences with regard to how the incentive scheme is applied across loan officer gender, i.e., female loan officers are compensated in the same way as male loan officers. In robustness tests below, we use alternative arrear probability definitions of 15 and 60 days. We also use the ratio of total repayments to contracted repayments as an alternative performance measure. The results remain when this performance measure is used instead of the arrear probability.

[9] Arrear or default frequencies are common in the literature to assess loan officer performance (e.g. Agarwal and Wang, 2009). Besides that, default frequencies are also used to assess the performance of rating agencies (e.g. Carty and Liebermann, 1997). On a more general level, survival rates are used to assess clinical trials, doctoral skills, and medical procedures.

2.2 SAMPLE CONSTRUCTION

We restrict and cut the data in several ways. For the main analysis, we restrict our attention to actual borrowers and their arrears and thus drop unsuccessful loan applicants. Second, we focus on a set of borrowers that have had only one loan with the bank, for several reasons. The first reason is that the database we use is constructed in a way that all socio-demographic borrower data are overwritten whenever a new loan application is submitted by a customer that had already applied for a loan before. Hence, some of the socio-demographic data we use as control variables might not be up to date if we use first loans from borrowers with further subsequent loan applications.[10] The second reason is that the comparison of first (and at the same time last) loan applications allows for a consistent comparison because all loan officers have the same limited information about the respective borrower at the time of the application. In the case of repeat borrowers, loan officers already have historic information, which they can take into consideration when granting and monitoring the loan. Focusing on the first loan by each successful loan applicant thus allows us to study in a clean way gender-specific loan officer performance differences.

Third, we drop 16 loans with missing gender information on the loan officer level. For the same reason, we exclude loans by borrowers classified as legal entities in the database because in these cases we cannot observe the borrowers' gender information. We will use the sample of

[10] For instance, a certain customer might have applied for a loan in 1996 when she was not married and again in 2000 when she was married. As the data we use were provided by the lender in January 2007, the database would classify that particular customer as being married also in 1996, although in 1996 this was not the case.

legal entities, however, as control sample in our exploration of the mechanisms below. Fourth, we drop loans with amounts of less than 100 and more than 100,000 U.S. dollars. While very low values might result from false entries in the database we want to exclude very large loans that do not fit the definition of small individual, SME or microloans.[11] In addition, we exclude loans with an unreasonable borrower age (younger than 18 or older than 75 years). Finally, we exclude loans approved in December 2006 as we cannot observe these loans' performance. This reduces our sample to 6,775 loans granted by 141 loan officers for the baseline regression analysis. Of these 141 loan officers, 83 (58.9 percent) are female and 58 are male. In robustness tests below, we use different cuts of the data. Combining all analyses with different data cuts we use close to 31,000 loan applications and around 26,500 loans.[12]

As robustness test and to show that our results hold beyond the Albanian case, we use data from a second subsidiary of the same lender in Bolivia. Specifically, for the baseline regression we have data for 7,772 approved borrowers over the years 2004 to 2006, granted by 195 loan officers, 87 (45.4 percent) of who are female. Unlike in the Albanian case, we do not have information on rejected applicants. While presenting the estimations with the Albanian

[11] Regression results are robust to this filter.

[12] In order to test for any biases that might arise from restricting our sample, we tested for significant differences between the original sample and the sample of first and last loans. We find that the fraction of first and last loans relative to all loans is, on average,24.4 percent for male and 26.5 percent for female loan officers, the difference, however, is not significant. While the share of loans in arrears is almost twice as high for the sample of first and last loans compared with the sample of overall loans, there is no significant difference between male and female loan officers in this respect.

sample as our main results, where possible we will also present results using the Bolivian sample.

2.3 IDENTIFICATION STRATEGY

To study performance differences between female and male loan officers, we exploit a random component of the dataset, the fact that assignment of first-time applicants to loan officers is independent of gender. We were assured by the data providing bank that an assignment of applicants to loan officers (or a choice of applicants by loan officers) is mainly based on the availability of the loan officers at the time the applicant appears at the bank. However, we carefully address the possibility that applicants assigned to female and male loan officers may differ with respect to personal, business-related or loan contract-related characteristics. For instance, female applicants might be overrepresented in certain business sectors and/or in certain regions, i.e., branches of the bank. If female loan officers are (for instance, because of specialization) also overrepresented in these business sectors, then the female applicants will have a higher likelihood to be matched with female loan officers. An unconditional higher likelihood of female applicants to be assigned to female loan officers would therefore not be due to the gender of the applicant, but to the business sector they operate in. Hence, to identify a gender-related performance difference, we test the identifying assumption that an assignment on gender does not take place controlling for only a few exogenous factors.

To formally test whether this assumption holds, we regress loan officer gender on applicant gender using all loan applications of first and last time applicants in Albania. This check shows whether female loan applicants are more likely to be matched with female loan officers after controlling for observable covariates and additional fixed effects. The covariates, which are described in the next section, comprise borrower location, loan destination, year fixed effects and the interaction of sector and branch fixed effects. Specifically, we estimate the Probit regression

$$Female\ loan\ officer_j = \alpha + \beta_1 * Female_i + \gamma * D_{ij} + \varepsilon_{ji} \qquad (1)$$

where *Female loan officer*$_j$ is a gender dummy taking the value one for female loan officers, $Female_i$ is a gender dummy taking the value one for female applicants, and D_{ij} is the vector of covariates. The coefficient of interest is β_1, showing whether applicant gender is related to loan officer gender conditional on the included covariates We cluster the standard errors at the loan officer level, thus allowing for unobserved correlation between loans processed and monitored by the same loan officer (Froot, 1989).

In the first column of Table I, we estimate specification (1) without any covariates, in column 2 we include covariates. While the female applicant dummy enters significantly in column 1, it turns insignificant once we control for the covariates in column 2. We obtain the same result when limiting the sample to only approved loans (column 3) in Albania and when using the sample of approved loans for Bolivia (column 4) where we do not have information on rejected applicants. In further unreported regressions, available on request, we estimate specification (1) for all other sample cuts that are used in this paper. We find that the female applicant dummy does not enter significantly in any of them. These results suggest that the assignment of loan applicants to loan officers is not based on gender and, hence, validate our identifying assumption.

2.4 SUMMARY STATISTICS

We include an array of loan officer, borrower, business and loan characteristics in the arrear probability regressions. Table II presents descriptive statistics for these variables for the Albanian sample, while Appendix Table AI presents them for the Bolivian sample. The descriptive statistics in Table II indicate that on average 13.5 percent of all loans in the baseline sample are in arrears for more than 30 days. 23.1 percent of the loans in our sample are given to female borrowers, while 57.7 percent are approved by female loan officers.[13] This seemingly high share of female loan officers is in line with recent labor market demographics from Albania. Specifically, labor market statistics for 2006 reveal that in the groups of technicians, professionals and clerks females constitute the majority with 57 percent. Digging deeper, we find that females constitute 56.3 percent of clerks and 52.6 percent of professionals, both categories most closely corresponding to our loan officers (Statistical Institute of Albania, 2007). Focusing on the gender distribution across sectors, a recent census (for 2008) finds that in the financial services sector the share of female employees is 52.3 percent.[14] These numbers are also in line with more recent cross-country data from 2009 from the World Bank and the Luxembourg Income Study that show that in major economies females are overrepresented in the financial services industry.[15]

In addition to the gender of loan officers, we include their age and the number of loan

[13] The share of loans approved and monitored by female loan officers does not vary substantially across the different sample cuts that we will use below.

[14] The census results are available upon request. We also checked the gender distribution for Bolivia. Data from the national bureau of statistics in Bolivia indicate that in the category Professionals and Office Workers, the share of women over the years 2004-2006 (our sample period in the Bolivian case) is 52.4 percent, thus close to the share of women in our sample of loan officers (45.4 percent).

[15] We use the Gender Key Employment Indicators, which is the result of a joint collaboration between the Gender and Development Group of the World Bank and the Luxembourg Income Study. http://www.lisproject.org/key-figures/key-figures.htm (download as of October 19, 2011).

applications they have processed since they started working for the bank. The 5 to 95 percent interval of the age of loan officers in our sample ranges from 21 to 29 years, with an average of 25 years. On average, loan officers have already processed 223 loan applications. In addition, we find considerable heterogeneity in their experience because the 5 to 95 percent interval of already processed loans ranges from 11 to 640 loans.

Further to controlling for the borrower's gender, we also control for her civil status, employment status (self-employed or – at least partly – employed wage earner) and age. We expect female, married and employed borrowers to be less likely to be in arrears for more than 30 days because of higher opportunity costs and more stable incomes. We also include the number of persons in the borrower's household, whether there is a phone available, and whether the borrower lives in or outside Tirana or La Paz. While the availability of a phone might increase the ease of monitoring by the loan officers and therewith reduce the arrear probability, there is no clear a-priori relationship between household size and arrear probability.[16] On the other hand we expect borrowers living outside of Tirana or La Paz and thus farther away from the nearest branch to have a higher arrear probability (DeYoung et al., 2008).

Our results show that, on average, borrowers are 39 years old, 75.4 percent of borrowers are married, while 87.6 percent are at least partly employed wage earners. On average, there are almost five persons in a borrower's household, there is a phone available in 93.2 percent of borrowers' households, and 79 percent of the borrowers live in Tirana. We find that leverage, defined as the total debt over total assets of the borrower at the time of the loan application is

[16] In the Bolivian sample, all borrowers have a phone. We do, thus, not include this variable in the respective regressions.

relatively low, with 2.1 percent. Borrowers hold on average 9 percent of their assets in cash, total assets are 35,000 USD, and monthly business profits 663 USD, indicating the micro-enterprise nature of our borrowers.

We include the applied loan amount and the applied maturity as loan characteristics in our baseline regressions. On average, borrowers apply for 4,212 U.S. dollars and a maturity of close to two years. In a robustness test, we instead control for several, potentially endogenous, loan characteristics. Specifically, we control for the annualized interest rate, the approved amount and the maturity of the loan.[17] Further, we include the ratio of approved to applied loan amount and the type of guarantees/collateral (personal guarantees, mortgage collateral, or chattel collateral) provided.[18] We find an average interest rate of 13.8 percent. The average loan size is 3,729 U.S. dollars while the average loan maturity equals to 16 months. On average, borrowers received 88.8 percent of the amount they applied for.[19] 96.2 percent of all loans were secured with chattel collateral, while 12.4 percent of all borrowers provided mortgage collateral and 15.0 percent personal guarantees.

The use of loan proceeds varies widely, with 26 percent of loans for home improvement, 11 percent of loans going into working capital, 21 percent to fixed asset purchases, 9 percent for

[17] Some loans in the database mature after 2006. These loans' maturity was adjusted to December 31, 2006 in order to be able to compare the outstanding loans with already matured loans.

[18] The use of chattel collateral is quite common in countries like Albania and Bolivia as objects from the household of a borrower (such as a fridge or a television) often have very high (not necessarily monetary) value for the borrowers.

[19] We winsorize the approved share at the 1st and 99th percentile to eliminate outliers.

mixed business (which is a combination of working capital and fixed asset purchases), and 33 percent for consumption purposes. In terms of sector distribution, we find that 18 percent of loans go to entrepreneurs in the construction sector, 9 percent in production, 20 percent in trade, 4 percent in transportation and 48 percent in other services.

The descriptive statistics in Appendix Table A1 indicate partly similar, partly different characteristics of our Bolivian sample. Arrears are much higher, with 30.4 percent. Female borrowers constitute the slight majority in the Bolivian sample (50.8 percent), while female loan officers also constitute almost half of the sample (45.4 percent) and loan officers are younger than borrowers, as in the Albanian sample. In addition, applied amounts are lower and applied maturities are shorter in Bolivia than in Albania.

Interestingly, we further find that loans granted by female loan officers have significantly lower arrear rates than loans granted by male loan officers. The average arrear probability of female loan officers in Albania is 12 percent. This contrasts to 15.7 percent for male loan officers.[20] If we compare the gender-gender combinations of borrowers and loan officers, we find that female loan officers have an average arrear rate for female borrowers of 7.8 compared with 11.5 percent for male loan officers. For male borrowers, on the other hand, the arrear rate of female loan officers is 13.5 percent compared with 16.6 percent for male loan officers. The comparisons are similar with respect to the loan officer gender differences in Bolivia, with an arrear rate of 24.9 percent and 37.8 percent for female borrowers in the case of female and male loan officers, respectively, and arrear probabilities of 22.2 and 34.4 percent for male borrowers.

[20] For the overall sample of loans, without the filters described, these ratios are 8.2 and 6.6 percent for male and female loan officers, respectively.

3. Methodology

We use two main baseline specifications to disentangle the relationship between arrear probability and the gender of borrowers and loan officers. Specifically, for the first set of results we utilize a binary Probit model of the following form:

$$Arrear_i = \alpha + \beta_1 * Female_i + \beta_2 * Female\ loan\ officer_j + \gamma * D_{ij} + \delta * Female_i * D_{ij} + \varepsilon_i \quad (2)$$

where $Arrear_i$ is a binary variable taking the value 1 if borrower *i* was in arrears for more than 30 days once during the lifetime of the loan, $Female_i$ is a dummy variable taking the value 1 for female borrowers, *Female loan officer*$_j$ is a dummy variable taking the value 1 if the loan officer *j* serving borrower *i* is female, D_{ij} is a vector of control variables referring to borrower and loan *i* and officer *j*, $Female_i*D_{ij}$ is a vector of interaction terms between the gender of borrower *i* and all covariates, and ε_i is an error term. The covariates are discussed in section 2.4. Consistent with equation (1), we include interactions between sector and branch fixed effects to control for potential clustering of loan officers or borrowers of a certain gender or ability in a specific sector and branch, year fixed effects to control for macroeconomic factors that might affect the arrear probability of borrowers, and loan destination fixed effects to control for risk differences associated with the loan usage. Results for these additional controls will be omitted from the tables. As above, standard errors are clustered at the loan officer level.

Given that loan officers may have superior screening or monitoring capabilities for borrowers of the same gender, our second set of baseline results utilizes several interaction terms to disentangle the relationship between arrear probability and gender pairs of borrower and loan officer:

$$Arrear_i = \alpha + \beta_1 * Female_i * Female\ loan\ officer_j + \beta_2 * Male_i * Female\ loan\ officer_j + \beta_3 * Male_i * Male\ loan\ officer_j + \gamma * D_{ij} + \delta * Female_i * D_{ij} + \varepsilon_i \quad (3)$$

The combination female borrower-male loan officer is the omitted category. The coefficient β_1 thus indicates whether female borrowers are more or less likely to be in arrears for more than 30 days with a female than with a male loan officer, while the difference between β_2 and β_3 indicates whether male borrowers have a lower arrear probability with a female than with a male loan officer. This specification therefore allows us to not only control for the correlation between borrower and loan officer gender, but also to distinguish between the performance difference of female and male loan officers among borrowers of different genders.

4. Main Results

This section reports and discusses our main findings, using the two regression models described above, and tests the robustness of the results with regard to the use of different samples and specifications. In order to draw conclusions about the economic as well as the statistical significance of our results, all results we report in this section are marginal effects, that is, the differences are absolute percentage changes.[21]

4.1 BASELINE REGRESSIONS

The results in column 1 of Table III suggest that borrowers served by female loan officers are less risky. The arrear probability of borrowers served by female loan officers is 4.6 percent lower than

[21] As we are using interaction terms of dummy variables, we compute the marginal effect as the actual change from zero to one.

the arrear probability of borrowers served by male loan officers across our sample of first (and last) loans. This effect is economically significant, given that the average arrear rate in our sample is 13.5 percent.

Several loan officer, borrower and loan characteristics enter significantly in the column 1 regression of Table III. First, older borrowers and borrowers served by older loan officers have a lower arrear probability. The latter result contradicts the career concern hypothesis by Agarwal and Wang (2009), but is in line with Andersson (2004). Second, married borrowers and borrowers from households where a phone is available are less likely to be in arrears for more than 30 days, suggesting higher opportunity costs for these borrowers. Third, borrowers living outside Tirana have a higher arrear probability. Fourth, borrowers with a higher cash-to-assets ratio and with higher total assets are less likely to default. Finally, we find that female borrowers are less likely to fall into arrears even after interacting all explanatory variables with a female borrower dummy, even though this effect is significant only at the 10% level.

The results in column 2 of Table III show that the performance advantage of female loan officers is robust to controlling for the correlation between loan officer and borrower gender and holds for both female and male borrowers. Compared to female borrowers monitored by male loan officers, female borrowers monitored by female loan officers have an arrear probability that is 4.7 percent lower. Similarly, testing for the difference between male borrowers with female loan officers and male borrowers with male loan officers, we find that the arrear probability of male borrowers is 5.1 percent lower for female loan officers. Both results are statistically and economically highly significant suggesting that, independent of the gender of the borrower, female loan officers are better in managing loan risk. Our findings on the different loan officer, loan and borrower characteristics are confirmed by this regression.

Columns 3 to 5 of Table III demonstrate the robustness of our results to using an alternative arrear probability definition and alternative samples and specifications. First, using the 60 day arrear definition we confirm our previous finding that female borrowers monitored by female loan officers have a lower arrear probability than female borrowers monitored by male loan officers, though with a smaller economic effect (that corresponds to the lower arrear probability at 60 days of 8.4 percent; see column 3).[22] The difference in arrear probability between male and female loan officers in the case of male borrowers, on the other hand, turns insignificant. Second, we do not restrict our attention to the first loans that were at the same time the last loans by the borrowers, but we use all first loans available in the database. As in this case we cannot be sure that the socio-demographic information did not change after the first loan, we exclude all socio-demographic variables from the regression. This less strict cut of the data yields a sample containing 14,003 first loans. We confirm our findings of significant differences between borrowers assigned to female and male loan officers, both for female and male borrowers (column 4). Third, we confirm our findings for the original sample of first and last loans and arrear probability of 30 days but including arguably endogenous loan contract terms, such as interest rate, the approved amount and maturity, the ratio of approved and applied loan amount, and collateral type. Controlling for these loan characteristics, we confirm our finding that

[22] In unreported regressions, available on request, we also use the 15 day cut-off and confirm our findings for both male and female borrowers. We also run linear regressions using an outcome measure ranging from 0 to 60 days (arrears higher than 60 days are coded as 60) and confirm all results. Looking beyond 60 days of arrears does not make sense in our context, as a loan file is transferred to a special unit after 60 days of arrears. We do not have information on the gender of those special loan officers.

both female and male borrowers have a lower arrear probability when assigned to a female rather than male loan officer (column 5).

In the analyses above, we measure loan officer performance by using the probability of a loan to be in arrears for more than 30 days. A potential issue with this variable is the problem of right censoring or truncation. As discussed above, we include loans that were originated in our sample period but have not matured before the end of it. This might introduce a certain bias as these loans are mechanically less likely to go into default because we cannot observe them over their whole life. We run two tests to address the potential bias stemming from measuring loan officer performance in this way. First, in column 6 we estimate our baseline regression using only 4,273 loans that were terminated before the end of our sample period, i.e., December 31, 2006. By definition, these loans do not suffer from a truncation problem. As can be seen, the results remain for both female and male borrowers. Second, in column 7 we report hazard rates of a Cox Proportional Hazards Model that estimates the time to the first payment delay over 30 days. To estimate this model we use additional data provided by the bank on actual loan repayments. Again, our main findings are confirmed.

The column 8 results of Table III, finally, confirm our findings for the Bolivian sample. Both female and male borrowers are less likely to fall into arrears if screened and monitored by a female than by a male loan officer. The higher economic effects of 14.1 and 10.6 percent can be explained with the higher unconditional arrear probability in the Bolivian sample (30.4 percent).[23]

[23] In unreported robustness tests, available on request, we assess whether our results for Bolivia suffer from truncation bias. Specifically, we ran the Table III Columns 6 and 7 specifications for the Bolivian data set and confirm our findings.

4.2 ROBUSTNESS TESTS

We next present and discuss the results of a series of additional tests to illustrate the robustness of our findings from the baseline regressions. First, we loosen the sample selection criteria and confirm our baseline results for different samples. Second, we confirm our findings for an alternative performance measure, using expected profitability as performance indicator. Third, we discuss the results using the Abadie and Imbens (2011) bias-adjusted propensity score matching estimator.

4.2.1 Different Samples

In the first robustness test, we loosen the sample selection that we had chosen for our baseline regression. Rather than first loans we use a sample of borrowers' repeat loans. This allows us a robustness test in two directions: on the one hand we expect a less significant relationship between the gender of the loan officer and arrear probability because the information asymmetries and thus agency problems between bank and borrower should be lower in the case of a repeat loan. On the other hand, by testing the robustness of our finding in a sample of repeat loans, we assess whether our findings can be explained by female loan officers having to focus on first-time borrowers rather than being able to focus on borrowers with an established bank relationship. In addition, repeat borrowers have identified themselves as low-risk borrowers and there is less variation in arrears to be explained. We also include several control variables that capture a borrower's loan history with the bank.[24] Specifically, we control for the duration of the lending relationship in years[25], whether any previous loan application of the borrower has been rejected and whether the borrower has ever been in arrears for more than 30 days on any loan granted by the lender before applying for a new loan. As in the baseline regression, we first focus on a sample of last loans to be able to control for socio-demographic borrower characteristics. Cutting the data in this way yields 6,375 repeat loans. Including all repeat loans yields a sample of 12,538 loans. In the case of Bolivia, we have a sample of 8,061 repeat last loans and 14,017 total repeat loans. Note that these samples are entirely different from the sample used in the baseline regression as the latter only included first loans. Further note that, to be consistent with the results from the baseline regressions in Table III, we focus on the identical set of 141 loan officers that we used before in the case of Albania and on the 195 loan officers used before in the case of Bolivia.

The results in column 1 of Table IV confirm the previous findings and their interpretation with a regression using repeat instead of first loans. We continue to find that female borrowers screened and monitored by female loan officers have a lower arrear probability than if screened and monitored by male loan officers, while, on the other hand, there is no significant difference for male borrowers anymore. However, even in the case of female borrowers, the economic significance is substantially smaller than before, with only 0.8 percent, compared to the 4.7 percent we found in column 2 of Table III. The results in column 2 of Table IV confirm these

[24] While many borrowers end up with different loan officers in repeat loans, there is no policy of intentional rotation at this financial institution.

[25] Results remain unchanged if we use the number of previous loans instead.

findings for the larger sample of repeat loans that is not limited to the last loan of each borrower. As before, we do not use the socio-demographic borrower characteristics for these regressions. The column 2 results show that the performance advantage of female vis-à-vis male loan officers is now only 0.9, while it is 1.8 percent for male repeat borrowers.

The column 3 and 4 results of Table IV show the same results for the Bolivian sample. In both the limited sample of last repeat loans and the broader sample of all repeat loans do we find a significant performance advantage of female over male loan officers in terms of arrear probability, both for female and male borrowers. As in the case of Albania, however, the economic effect is greatly reduced compared to the sample of first loans, with female loan officers having a performance advantage of 1.9 to 2.4 percent in the case of female borrowers and 2.1 to 2.3 percent in the case of male borrowers.[26]

Taken together, the results in Table IV suggest that the performance advantage of female vis-à-vis male loan officers continues to hold for repeat loans, although in the case of Albania it is more pronounced for female borrowers. Critically, however, we find that this effect is smaller compared with first loans.

We ran additional unreported robustness tests (available on request) to demonstrate that

[26] In unreported regressions, we combine first and subsequent loans by the same borrower and estimate specification (3) for the combined sample, including a variable indicating the number of the approved loans by each borrower. In the first case, we focus only on the last loans in order to be able to use the socio-demographic data, and in the second case we use all approved loans in the sample without including socio-demographic data. For both samples and for both Albania and Bolivia, we continue to find that female loan officers have statistically and economically significantly lower arrear rates than male loan officers for female as well as for male borrowers.

the effect we documented is really driven by loan officer gender. First, we test whether the performance advantage of female loan officers is driven by a few top performers. We re-ran the Table III column 2 baseline regression using only loans screened and monitored by the two lower performance terciles of loan officers, i.e. excluding the top performers. The results are confirmed for both female and male borrowers. Second, we drop loans granted by loan officers in their first two years at the bank for the Albanian sample to require a minimum level of lending experience. Baseline results are very similar for these more experienced loan officers. Third, we exclude loans granted in the years 1996 and 1997 from the Albanian sample to exclude the effects of the bank's start-up phase and the pyramid scheme crisis that hit Albania in early 1997. Again, our main baseline results remain unchanged for this smaller sample. Fourth, we restrict our sample to business loans, i.e. either loans for working capital or fixed assets (or a combination of the two). Our baseline results remain unchanged for Albanian and Bolivian business loans. Fifth, we split our baseline samples with respect to the approved loan amount and run separate regressions for loan sizes above / below the median. The baseline results are very similar for both Albania and Bolivia.

4.2.2 Use of an Alternative Performance Measure

Second, instead of using arrear probability as dependent variable, we employ two alternative performance indicators to demonstrate that the performance gap between female and male loan officers is not due to the use of a specific performance gauge. Rather than focusing on arrears, here we focus on actual repayments. Unfortunately, we do not have recovery rates on defaulted loans, but were assured by the bank that these are minimal given the small loan amounts, which does not justify going to the courts. As it is not the loan officers screening and monitoring the loans who are responsible for recovery of defaulted loans, we have no reason to believe that these small recovery rates vary systematically between male and female loan officers.

Specifically, we can distinguish between capital repayments relative to the total loan amount (*Rec1*) and interest plus capital (re)payments relative to the total loan amount plus expected interest payment (*Rec2*). By including interest rates, we can also specifically control for the risk-return trade-off of lower interest rates with lower arrear risk. In the case of Albania, the ratio of repayments to capital is, on average, 97.7 percent, while the ratio of principal plus interest repayments to principal plus expected interest payments is, on average, 97.9 percent. In the case of Bolivia, these two ratios are 93.9 and 94.4 percent, respectively. In Table V, we test whether the column 2 (8) of Table III results hold for Albanian (Bolivian) borrowers when we use these two alternative performance measures.

For these tests, we use a Tobit regression because the dependent variables are truncated at 100 percent. Our samples are somewhat smaller because we do not have repayment information for all loans. The results in columns 1 and 2 of Table V confirm our finding of a performance advantage of female over male loan officers in Albania for both female and male borrowers. The results in columns 3 and 4 confirm our finding of a performance advantage of female over male loan officers in Bolivia for both female and male borrowers.[27] In all cases, the total repayments are higher for borrowers matched with female loan officers than with male loan officers.

4.2.3 Propensity Score Matching

[27] We also ran the regressions of Table V using only terminated loans to rule out any truncation bias. The results remain economically and statistically highly significant.

Our identification strategy relies on the assumption that borrower assignment to loan officers is independent of gender, a formal test for this assumption was provided in section 2.3. In this subsection, we nevertheless describe the result of an additional robustness test that takes into account concerns that selection based on (observable) borrower characteristics may be a main driver of our results.

Specifically, we make use of the Abadie and Imbens (2011) bias-adjusted propensity score matching estimator, which removes any conditional bias that may occur in simple nearest-neighbor matching estimators (Abadie and Imbens, 2006). We use the same matching variables as in column 2 (column 8) of Table III for Albania (Bolivia) to match observations across loan officer gender according to observable characteristics. We utilize an exact match with respect to the borrower gender to resemble our baseline regression setup of Table III. That way, we estimate the average treatment effect independent on borrower gender by comparing female to male loan officers for female borrowers and female to male loan officers for male borrowers.[28] We further choose the number of matches according to the simulation results in Abadie and Imbens (2011) who find the best matching quality for the number of four matches.

We get almost identical results as the ones shown in our baseline regressions in Table III. If any, results appear economically and statistically stronger by using the propensity score matching. We furthermore investigate the quality of the propensity score matching. While we

[28] Note that we thus do not need to include the covariates*Female interaction terms. Results remain qualitatively unchanged if we also include these interaction terms and do not require an exact match with respect to the borrower gender.

achieve a reduction in the median of the absolute standardized bias[29] of around 30 percent for Albania, the reduction is even around 70 percent in the case of Bolivia.

All in all, the propensity score matching results support our baseline findings that borrowers handled by female loan officer are less likely to delay repayment. It also adds further credibility to our overall identification strategy.

5. The Gender Performance Gap – Exploring the Mechanisms

The results reported in the previous section suggest a significant performance advantage of female loan officers, though more robust for female borrowers, a distinction we will get back to below. This section explores possible mechanisms that can explain this finding. Specifically, we test whether female loan officers are better at screening, have a lower workload, are more experienced, or are also better with legal entities.

5.1 SCREENING

The superior performance of female loan officers may be attributable to their better screening capacities and/or effort. For instance, if female loan officers are better in screening, then they will have a better pool of clients after loan approval. This, in turn, could explain their lower share of loans in arrears for more than 30 days. A better screening ability may have two sources. It may be

[29] The standardized bias is the difference of the sample means in the treated and non-treated (unmatched or matched) sub-samples as a percentage of the square root of the sample variances in the treated and non-treated groups (Rosenbaum and Rubin, 1985). In our case the treated group consists of approved loans handled by female loan officers, while the non-treated group consists of approved loans handled by male loan officers.

based on observable and on unobservable applicant characteristics (and a combination of the two). Alternatively, female loan officers might simply be more restrictive because they are more risk averse (e.g. Sunden and Surette, 1998; Agnew et al., 2003). In either case, we would expect that female loan officers should be more likely to reject applicants. To test whether differences in screening drive our results we use a sample containing both approved and rejected loan applications and run the following regression

$$Approval_i = \alpha + \beta_1 * Female_i * Female\ loan\ officer_j + \beta_2 * Male_i * Female\ loan\ officer_j + \beta_3 * Male_i * Male\ loan\ officer_j + \gamma * D_{ij} + \delta * Female_i * D_{ij} + \varepsilon_i \tag{4}$$

where $Approval_i$ is a dummy variable indicating whether a loan application was approved or not. We can run regression (4) only for Albania because we do not have data on rejected applicants from Bolivia.

We test for screening differences using four different samples. First, we use a sample of first and last loan applications with 8,187 loan applicants,[30] around 93 percent of which were accepted. Second, we drop the socio-demographic variables and include all first loan applications, yielding a sample of 15,827 loan applications. Third, we use a sample of repeat applicants. Again, we run a specification with loan applications that were at the same time last loan applications (sample size of 7,590 loan applications) and a specification without this restriction and, thus, without socio-demographic applicant characteristics (14,763 loan applications).

The results in Table VI suggest that our finding of a superior performance of female vis-à-vis male loan officers is not driven by differences in screening. We do not find any significant

[30] Here we also include loans approved in December 2006, unlike for the arrears regressions.

difference in the likelihood of borrowers to be accepted by female or male loan officers, independent of whether the borrower is male or female, except the columns 3 and 4 results where we find that female loan officers are (weakly) less likely to accept repeat loan applications of male clients.

Furthermore, in unreported regressions, we tested for differences across loan officer gender using alternative loan contract terms. For instance, it might be argued that female loan officers anticipate that their borrowers are less likely to go into arrears and that this is reflected by more favorable loan characteristics such as lower interest rates. Specifically, we replaced the arrear probability variable with the annualized interest rate, with the approved maturity and the share of approved over applied loan amount, all three being direct loan contract terms that are decided by the loan officer. We did this for female and male borrowers for both Albania and Bolivia. Only in the case of male borrowers in Bolivia there is a significant difference between female and male loan officers. In particular, female loan officers grant male borrowers loans with shorter maturities than male loan officers. For all other loan outcomes, there are no loan officer gender-related differences. We thus find no evidence that female loan officers anticipate the lower arrear likelihood of their borrowers.

Taken together, these results suggest that female loan officers are not more risk averse in their approval decisions based on observable applicant characteristics and also do not seem to anticipate that their borrowers go less often into arrears. Moreover, we investigate whether female loan officers screen borrowers more diligently by analyzing the time between the loan application and the approval decision across loan officer gender. Differences between female and male loan officers are not significant. These results suggest that screening differences between female and male loan officers do not seem to drive the performance gap between them.[31]

While we do not find any screening differences between female and male loan officers based on observable applicant characteristics, it may be that they differ with regard to screening based on characteristics that we do not observe in the data. One way to address this is to focus on those applicants who were screened by both a female and a male loan officer and analyze whether the approval likelihood differs in both cases. This is a stronger test than before where we compared different applicants assigned to different loan officers as here we are focusing on the same applicant screened by loan officers of different genders. Specifically, we identify all applicants screened and rejected by a female loan officer, and subsequently screened by a male loan officer (and vice versa) because another loan application was submitted.[32] We then compare the approval likelihood of these applicant groups. The rationale for this test is to analyze whether the approval likelihood of the same applicant is different when she is screened by a female compared to when she is screened by a male loan officer. For this analysis, a simplifying assumption that we make is that neither observable nor unobservable applicant characteristics changed between the rejected and the subsequent (rejected or approved) loan application, a reasonable assumption given that the median time between the two applications is 240 days.

[31] This result matches the finding by Agarwal and Wang (2009) who do not find any significant difference in acceptance decisions between male and female loan officers for a borrower sample from a U.S. bank.

[32] The bank does not have a routine loan officer rotation in place, but borrowers may be served by different loan officers in further loan applications because loan officers leave the bank, change the position in the bank, or may be absent on the day the borrower submits another application.

Besides making this assumption, we control for several variables that may have changed between the first and second loan application by the same applicant. For instance, we include the time in days between the first and second application, the change in the experience of the loan officer between both applications, and the change in the applied amount between the first and the second loan application. Concerns regarding the assumption that borrower and loan characteristics could change between both applications should be addressed by this. Any differences in the approval likelihood should then be driven by unobservable applicant characteristics that are taken into account differently by female and male loan officers.

Identifying such borrowers yields a sample of 901 loan applications. We find that the approval ratio for applicants that were first rejected by a male loan officer, submitted another loan application, and were then screened by a female loan officer is 75.1 percent. On the other hand, the approval ratio for applicants that were first rejected by a female loan officer, applied again, and were subsequently screened by a male loan officer is 79.6 percent. The difference is not significant. Running a regression with the approval dummy as dependent variable and the control variables we used in the Table VI column 1 screening regression, applicants that are first screened and rejected by a female loan officer do not have a significantly higher likelihood to be approved by a male loan officer if they apply for another loan than vice versa.[33] These results suggest that female loan officers do not screen loan applications more conservatively after accounting for unobservable applicant characteristics.

All in all, we find no evidence that female loan officers screen differently than male loan

[33] Results are available on request. We furthermore restrict the sample to only include loan applications for the same loan type. The difference of the approval likelihood remains insignificant.

officers based on observable and unobservable applicant characteristics. This result suggests that different screening techniques are not the mechanism driving the performance differences between female and male loan officers.

5.2 DIFFERENCES IN WORKLOAD

Differences in the workload of female vis-à-vis male loan officers may also explain the superior performance of female loan officers we established in section 4. For instance, if male loan officers worked significantly more than female loan officers, this might reduce the screening and/or monitoring intensity per borrower and, eventually, the performance of male loan officers. We may think of two reasons why male loan officers work more than female loan officers. First, it may be a decision of the bank to assign more loan applications and therewith, given that the approval ratios are not different between male and female loan officers, more borrowers to male loan officers. Second, male loan officers may volunteer to handle more loan applications, which could be interpreted as sign of a higher degree of overconfidence of male loan officers that was previously documented in the literature (e.g. Barber and Odean, 2001; Niederle and Vesterlund, 2007).

To test for differences in workload between male and female loan officers we first calculate the number of loan applications handled by either loan officer type separately for different time intervals. For instance, we compare how many loan applications male loan officers handled in their first year with the bank with the number of loan applications handled by female loan officers in their first year. We then do the comparison for the first two years, three years, etc. The time intervals are constructed by using the dates on which the respective loan officer handled the first and the last loan application. This allows us to approximate the time the respective loan officer has worked for the bank. We then count the number of loan applications handled over this time horizon and do a standard (one-sided) t-test for differences. In the case of Albania, we do this separately for all loan applications received, i.e., all screened and monitored loans, as well as for all approved loans, i.e., only monitored loans, while in the case of Bolivia, we can only analyze approved loans. We focus on the 141 Albanian and 195 Bolivian loan officers included in our sample for the baseline regression. In order to measure their workload comprehensively, we do not exclude any loan applications or approved loans because of missing data for the independent variables. Hence, these tests are based on all loan applications or approved loans included in the database.

The results in Panel A of Table VII show that, although male loan officers in Albania tend to have a slightly higher workload, none of the differences is statistically significant at conventional levels and as measured by one-sided t-tests. The results in Panel B suggest that female loan officers have a higher workload in Bolivia, though the difference is only marginally significant at the 10 percent level for loan officers during their first year. This suggests that the performance differences we detected are not driven by female loan officers having fewer borrowers to screen and to monitor.

5.3 LOAN OFFICER EXPERIENCE

We now explore how gender differences in loan officer performance change with experience because this may provide some guidance on how gender and experience interact in loan officers' "production function". For that purpose we add to specification (3) three-way interaction terms between the borrower-loan officer interaction dummy of interest and a variable approximating for the loan officer's experience. Specifically, we control for loan officer experience by interacting the borrower-loan officer gender with the number of loan applications the loan officer has already handled before this specific loan.

$$\begin{aligned} Arrear_i = \alpha + \beta_{1,1} * Female_i * Female\ loan\ officer_j + \beta_{1,2} * Female_i * Female\ loan\ officer_j * Applications_j + \\ \beta_{2,1} * Male_i * Female\ loan\ officer_j + \beta_{2,2} * Male_i * Female\ loan\ officer_j * Applications_j + \\ \beta_{3,1} * Male_i * Male\ loan\ officer_j + \beta_{3,2} * Male_i * Male\ loan\ officer_j * Applications_j + \gamma * D_{ij} + \delta * Female_i * D_{ij} + \varepsilon_i \end{aligned} \quad (5)$$

The sign and significance of the coefficient $\beta_{1,2}$ indicates whether and how the performance advantage of female loan officers varies with their experience. If experience differences drive the superior performance of female loan officers, we expect to find a negative and significant triple interaction term. Table VIII contains the results of these regressions. We run specification (5) both for the Albanian and the Bolivian sample.

The column 1 regression of Table VIII shows that in Albania the advantage of female loan officers in managing the loan risk of female borrowers is independent of the experience of the loan officer. While *Female*Female loan officer* enters negatively and significantly, the triple interaction term with experience of the loan officer does not enter significantly. For male borrowers, on the other hand, we find clear evidence for an experience effect. The difference between the combination of male borrowers with female and with male loan officers is insignificant, but the triple interaction term with loan officer experience is negative and significant. This indicates that for low experience levels, there is no performance gap between female and male loan officers for male borrowers, but as experience increases, the performance gap associated with the combination female loan officer and male borrower vis-à-vis male loan officer with male borrower widens.

The column 2 regression of Table VIII confirms these findings for the Bolivian sample. Specifically, the performance advantage of female loan officers among female borrowers does not vary with experience, while the performance advantage of female loan officers among male borrowers is again a function of their experience.

In unreported robustness tests (available on request), we also re-ran the column 2 regression of Table III separately for first-year loan officers, first and second year loan officers and first, second and third year loan officers. We find that the performance advantage of female loan officers with female borrowers holds for all three subgroups, while the performance advantage of female loan officers with male borrowers holds only for the subgroup of all first, second and third year loan officers.[34]

Summarizing, we find a striking difference between male and female borrowers concerning the performance advantage of female loan officers. While female loan officers always have a performance advantage among female borrowers, independent of their experience, their performance advantage among male borrowers develops over time, with experience.

5.4 DIFFERENCES IN BORROWERS' LEGAL STATUS

We finally test whether the female loan officer advantage also holds for legal entities. In the case of legal entities, it should be more difficult to establish a trust relationship for the loan officers, as legal entities are usually larger, decisions are more complex and usually involve more people. We

[34] These results also offer an indirect test for unobserved loan officer ability: female loan officers should outperform their male peers if female loan officers' abilities were higher when they start working for the bank. One could argue that ability would make up for the lack of experience at the beginning. Over time, male loan officers should be able to catch up with female loan officers with increasing experience as ability should decline in importance. This, however, is not the case. We interpret these results as evidence that unobserved ability is not different between female and male loan officers.

thus repeat the Table III column 1 regression for samples of legal entities and contrast the findings to the findings for natural entities where the borrower gender can be identified. Again, this analysis can only be done for the Albanian sample because we do not have a sufficient number of legal entities in the Bolivian dataset.[35] We do this for three subsamples: all first and at the same time last loans, therewith corresponding to our baseline sample, all first loans, and all loans. The reason why we also include the latter two subsamples is that the sample size becomes very small in the case of legal entities when using only the baseline sample. Also, we cannot use the loan officer-borrower gender interaction terms because in the case of legal entities there is no borrower gender. Thus, we focus on the loan officer gender dummy. The results are contained in Table IX.

They show clear differences between the samples of natural and legal entities. The female loan officer dummy does not enter significantly in any of the three subsamples containing only legal entities, while it enters significantly in all subsamples of natural entities with a negative sign. This provides additional support for the hypothesis that female loan officers seem to be better than male loan officers because they seem to be better at establishing trust relationships, particularly among the female borrowers. This interpretation is obviously subject to the caveat of possible measurement bias stemming from the fact that we cannot observe the gender of the loan officer's counterpart and/or owner at the borrowing legal entity.

One additional piece of evidence lends support to our suggestive finding that female loan officers seem to be better at building trust relationships. In our sample period, there was no

[35] Specifically, we have only 23 legal entities with first loans in our Bolivian sample.

mandatory, public credit registry in Albania (this was only introduced in January 2008), while in Bolivia there was. As the performance advantage of female loan officers holds in both countries, it seems to have less to do with hard information that can be compiled in a credit registry. This suggests that other factors seem to play a bigger role, which is consistent with the story that female loan officers are better at establishing trust relationships with their clients.

All in all, these pieces of evidence suggest that female loan officers do not seem to be universally better than their male peers. They seem to do better in situations in which a trust relationship can be more easily established and maintained. Such a relationship is easier where female loan officers deal with natural persons rather than legal entities and where they deal with their own gender. In the case of male borrowers, on the other hand, the experience to build a trust relationship has to be acquired over time. This is also consistent with the experience results in Table VIII.[36] In addition, availability of hard information does not seem to drive our results, since there was no public credit registry during our sample period in Albania while there was one in Bolivia.

6. Conclusions

This study is, to the best of our knowledge, the first to explicitly consider the role of the gender of the lender by analyzing performance differences across loan officer gender. Our main finding is

[36] One more alternative explanation could be that women react stronger to monetary incentives (recall that part of the salary of a loan officer at this bank is paid based on the share of loans in arrears), for instance because they have more dependent people in their households. In unreported regressions we rule out that loan officer household size or civil status explain our findings.

that gender indeed seems to matter in banking: female loan officers have statistically and economically significantly lower arrear probabilities associated with their borrowers. This novel result holds for both female and male borrowers, with the effect being more pronounced for female borrowers, and is robust to a series of additional tests.

Our analyses also shed light on the mechanisms through which female loan officers are more effective in reducing arrear likelihood. First, we do not find evidence that female loan officers have better screening abilities, controlling for and based on observable and unobservable borrower characteristics. This also suggests that female loan officers are not necessarily more risk-averse than their male colleagues. Second, we can rule out that male loan officers work significantly more than female loan officers and have, hence, less time to screen and monitor their borrowers. Finally, potential differences in experience of female and male loan officers do not seem to drive our results for female borrowers, though female loan officers only gain a performance advantage with male borrowers as they collect experience.

Our results are consistent with female loan officers being better in building trust relationships. We offer two pieces of evidence for this. First, female loan officers have always – independent of their experience – a performance advantage with female borrowers, while they build up this advantage with male borrowers only over time with experience. Second, female loan officers have no performance advantage with legal entities where establishing a trust relationship is more difficult. This is consistent with experimental evidence that women are more likely to agree with women in ultimatum games (Eckel and Grossman, 2001). It is also consistent with the results in Adams and Ferreira (2009) that women seem to strengthen monitoring when joining corporate boards and shows that in addition to career concerns, compensation schemes and information asymmetries (Agarwal and Wang, 2009), gender can play an important role in loan officer performance.

While we show the robustness of our findings for both Albania and Bolivia and our baseline findings match other authors' work for the U.S., we recognize that the results might vary across countries with the degree of labor market discrimination against women. A priori, however, it is not clear, which direction this would go; on the one hand, women might invest less in their human capital in countries with higher degrees of labor market discrimination; on the other hand, the few women who can overcome the discriminatory barriers, might excel even more.

The findings that female loan officers seem to perform better in managing their loans than male loan officers gives rise to the question why the bank continues to employ male loan officers. This can be explained by the fact that the bank plans to extend more loans to legal entities in the future and for these, as shown above, female loan officers do not perform better.

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Table I. Test of gender-independent borrower assignment

This table contains the marginal effects of Probit regressions with the female loan officer dummy (*Female loan officer*) as dependent variable (female = 1). The female borrower dummy (*Female*) is the main explanatory variable (female = 1). In column 1 we regress *Female loan officer* only on *Female*. In column 2 we then add sector*bank branch interaction terms and additional control variables. The latter include borrower location, loan destination, and year fixed effects. See Table II for a description of these covariates. The first two columns use all loan applications, while we restrict the sample to first and at the same time last approved loans in the third and fourth column. Standard errors are clustered at the loan officer level and are reported in parentheses. *,**,*** indicate significance at the 10, 5, and 1 percent level, respectively.

	Regression model			
Independent variables	I	II	III	IV
Female	0.1173***	0.0166	0.0134	0.0056
	(0.0216)	(0.0138)	(0.0157)	(0.0144)
Sector*Branch fixed effects	No	Yes	Yes	Yes
Additional control variables	No	Yes	Yes	Yes
Observations	8,187	8,187	6,775	7,772
Country	Albania	Albania	Albania	Bolivia
Type	Loan applications	Loan applications	Approved loans	Approved loans
Sample	First & last	First & last	First & last	First & last

Table II. Sample characteristics for Albanian borrowers

This table contains borrower, loan, and loan officer characteristics for 6,775 approved loans from the Albanian lender used in the baseline analysis. The table includes the first and last loan for each borrower. We further drop loans with unreasonable entries for the borrower's age (smaller than 18 or larger than 75 years), missing gender information for borrower and loan officer, and unreasonable entries for applied loan size (smaller than 100 or larger than 100,000 US dollars). The first column provides the means for all loans, while column 2 (3) provides the means for female (male) loan officers only. *Arrear* is a dummy variable indicating whether a borrower was in arrears for more than 30 days at least once over the whole lifetime of the loan, *Female* is a dummy variable indicating the gender of the borrower (female = 1), *Female loan officer* is a dummy variable indicating the gender of the loan officer (female = 1), *Loan applications per loan officer* is a loan officer experience proxy indicating the number of loan applications handled by the loan officer until the respective loan was granted, divided by 1,000, *Age of loan officer* is the age of the loan officer at the time the loan was granted measured in years, *Age of borrower* is the age of the borrower at the time of the loan application, *Civil status* is a dummy variable indicating whether the borrower is married (married = 1), *Wage earner* is a dummy variable indicating whether the borrower is self-employed or at least partly an employed wage earner (wage earner = 1), *Number persons household* indicates how many persons including the borrower are in the household of the borrower, *Phone availability* is a dummy variable indicating whether the borrower has a phone or not (phone available = 1), and *Borrower lives in Tirana* is a dummy variable indicating whether the borrower lives in or outside Tirana (in Tirana = 1). *Leverage* (total liabilities over total assets), *Cash over assets* (liquid assets over total assets), *Total assets* (in USD), and *Business profits* (monthly, in USD) are taken from the borrowers' financial statements. *Applied amount* is the loan size applied for by the borrower in US dollars while *Applied maturity* is the loan maturity in days the borrower applied for. *Interest rate* is the annual interest rate charged on the loan, *Approved amount* is the loan size granted in US dollars, *Approved maturity* is the loan maturity in days adjusted such that no loan has a maturity greater than December 31, 2006, *Approved share* is the ratio of applied amount to approved amount, *Personal guarantee, Mortgage collateral, and Chattel collateral* are all dummy variables indicating whether any of the three respective types of guarantees or collateral are pledged by the borrower. *Working capital*, *Fixed assets*, *Mixed business*, *Home improvements*, and *Consuming* are the loan destinations. The category *Mixed business* is a mix of working capital and fixed asset expenditures. *Construction*, *Production*, *Other services*, *Trade*, and *Transport* are the borrowers' business sectors. *Branch 1*, *Branch 2*, *Branch 3*, and *Branch 4* denote the borrowers' bank branches.

	Mean | Loan officer gender						
Variable	All	Female	Male	SD	5%	Median	95%
Arrear (30 days)	0.135	0.120	0.157	0.342			
Female borrower	0.231	0.270	0.177	0.421			
Loan officer characteristics							
Female loan officer	0.577	1.000	0.000	0.494			
Loan applications per loan officer	0.223	0.226	0.219	0.199	0.011	0.163	0.640
Age of loan officer	25	24	26	2	21	24	29
Borrower characteristics							
Age of borrower	39	39	40	11	24	38	58
Civil status	0.754	0.710	0.813	0.431			
Wage earner	0.876	0.955	0.768	0.329			
Number persons household	4.825	4.655	5.057	1.749	2.000	5.000	8.000
Phone availability	0.932	0.931	0.932	0.253			
Borrower lives in Tirana	0.790	0.872	0.678	0.407			
Business characteristics							
Leverage	0.021	0.022	0.019	0.077	0.000	0.000	0.152
Cash over assets	0.090	0.081	0.103	0.135	0.003	0.036	0.385
Total assets	35.040	37.561	31.603	47.868	2.207	22.371	105.189
Business profits	0.663	0.667	0.659	0.737	0.000	0.538	1.804

(Table II continued)

	Mean | Loan officer gender						
Variable	All	Female	Male	SD	5%	Median	95%
Loan characteristics							
Applied amount	4,212	4,527	3,783	6,284	610	2,872	13,853
Applied maturity	669	707	617	466	360	540	1,440
Interest rate	0.138	0.135	0.142	0.028	0.086	0.148	0.167
Approved amount	3,729	4,083	3,247	5,794	522	2,322	12,381
Adjusted maturity	488	517	450	264	130	450	933
Approved share	0.889	0.901	0.873	0.191	0.500	1.000	1.000
Personal guarantee	0.150	0.163	0.132	0.357			
Mortgage collateral	0.124	0.149	0.090	0.330			
Chattel collateral	0.962	0.951	0.977	0.190			
Loan destinations, sectors and branches							
Working capital	0.109	0.076	0.152	0.311			
Fixed assets	0.213	0.135	0.318	0.409			
Mixed business	0.088	0.035	0.160	0.283			
Home improvements	0.258	0.325	0.167	0.438			
Consuming	0.333	0.428	0.202	0.471			
Construction	0.184	0.211	0.146	0.387			
Production	0.094	0.039	0.170	0.292			
Other services	0.482	0.582	0.347	0.500			
Trade	0.197	0.139	0.275	0.397			
Transport	0.043	0.029	0.062	0.203			
Branch 1	0.405	0.469	0.319	0.491			
Branch 2	0.342	0.319	0.373	0.474			
Branch 3	0.150	0.194	0.089	0.357			
Branch 4	0.103	0.018	0.219	0.304			

Table III. Arrear probability and loan officer gender – first loans

This table contains results of the outcome test with the gender of borrowers and loan officers for loans from Albania (models I – VII) and Bolivia (VIII). We present marginal effects for Probit models except for model VII, which reports hazard rates from a Cox Proportional Hazards model. The models are based on sub samples of approved loans that are at the same time first and last loans per borrower except model IV, which comprises all 14,003 first loans from Albania and except model VI, which comprises only terminated first and last loans. For all models except III, the dependent dummy variable is the occurrence of a borrower being in arrears for more than 30 days at least once over the whole lifetime of her loan (1 if arrears > 30 days, 0 otherwise). Regression model III uses an arrear definition of 60 days. In models II to VIII, we interact the borrower and loan officer gender: *Female & Female loan officer* is a dummy variable indicating the combination of a female borrower and a female loan officer, *Male & Female loan officer* indicates the combination of a male borrower and a female loan officer, *Male & Male loan officer* indicates the combination of a male borrower and a male loan officer. Model V does not use potentially endogenous variables. We also control for loan destinations (working capital, fixed assets, mixed purpose, housing improvement, and consumption), year dummies, and business sector by bank branch fixed effects. We furthermore include interaction terms for all control variables with the female borrower dummy (*Female*). Results for these control variables and the interaction terms are omitted. The combination *Female & Male loan officer* serves as the reference group. A Wald test is used to analyze the null hypothesis that the difference between *Male & Female loan officer* and *Male & Male loan officer* equals zero. The independent variables are as described in Table II. Standard errors are clustered at the loan officer level and are reported in parentheses. *,**,*** indicate significance at the 10, 5, and 1 percent level, respectively.

	Regression model							
Independent variable	I	II	III	IV	V	VI	VII	VIII
Female	-0.1418*							
	(0.0570)							
Female loan officer	-0.0456***							
	(0.0152)							
Female & Female loan officer		-0.0466***	-0.0376***	-0.0219**	-0.0441***	-0.0661***	-0.6157***	-0.1421***
		(0.0144)	(0.0071)	(0.0097)	(0.0137)	(0.0227)	(0.2055)	(0.0331)
Male & Female loan officer		0.0530	0.0596	0.0966	0.0402	0.0676	2.1119	-0.2754*
		(0.1947)	(0.1471)	(0.1191)	(0.2204)	(0.3411)	(2.1192)	(0.1046)
Male & Male loan officer		0.1044	0.0815	0.1488	0.0869	0.1311	2.3303	-0.1695
		(0.2284)	(0.1797)	(0.1505)	(0.2573)	(0.3874)	(2.1301)	(0.1437)
Loan applications per loan officer	0.0364	0.0336	-0.0115	0.0185	0.0275	0.0581	0.2945	0.0352
	(0.0379)	(0.0377)	(0.0265)	(0.0252)	(0.0375)	(0.0530)	(0.3447)	(0.0550)
Age of loan officer	-0.0095***	-0.0087***	-0.0032	-0.0060***	-0.0078**	-0.0121**	-0.0454*	-0.0031
	(0.0029)	(0.0033)	(0.0021)	(0.0020)	(0.0031)	(0.0055)	(0.0244)	(0.0049)
Age of borrower	-0.0021***	-0.0021***	-0.0013***	-0.0016***	-0.0019***	-0.0030***	-0.0163***	-0.0029***
	(0.0004)	(0.0004)	(0.0002)	(0.0002)	(0.0004)	(0.0006)	(0.0043)	(0.0008)
Civil status	-0.0234**	-0.0233**	0.0008		-0.0239**	-0.0180	-0.1307	-0.0774***
	(0.0115)	(0.0115)	(0.0066)		(0.0115)	(0.0178)	(0.1223)	(0.0181)
Wage earner	0.0002	0.0004	-0.0066		-0.0019	-0.0211	-0.0811	-0.0920*
	(0.0160)	(0.0156)	(0.0126)		(0.0166)	(0.0299)	(0.2478)	(0.0471)
Number persons household	-0.0023	-0.0023	-0.0030**		-0.0034*	-0.0042	-0.0690***	-0.0013
	(0.0020)	(0.0020)	(0.0015)		(0.0019)	(0.0033)	(0.0255)	(0.0060)
Phone availability	-0.1024***	-0.1026***	-0.0297**		-0.0945***	-0.1319***	-0.3615***	
	(0.0372)	(0.0371)	(0.0146)		(0.0327)	(0.0484)	(0.1377)	
Borrower lives in Tirana	-0.0432***	-0.0433***	-0.0178**		-0.0396***	-0.0514***	-0.1517	
	(0.0138)	(0.0138)	(0.0090)		(0.0134)	(0.0210)	(0.1149)	
Borrower lives in La Paz								0.0481*
								(0.0283)

(Table III continued)

Independent variable	Regression model I	II	III	IV	V	VI	VII	VIII
Leverage	-0.0541	-0.0539	-0.0196	-0.0519	-0.0379	-0.0094	0.2909	-0.1296
	(0.0542)	(0.0541)	(0.0294)	(0.0322)	(0.0516)	(0.0814)	(0.4741)	(0.2169)
Cash over assets	-0.0857**	-0.0853**	-0.0397**	-0.0291	-0.0712**	-0.1445***	-0.1565	-0.0640**
	(0.0336)	(0.0336)	(0.0192)	(0.0183)	(0.0329)	(0.0555)	(0.3115)	(0.0272)
Total assets	-0.0003***	-0.0003***	-0.0003***	-0.0001**	-0.0002*	-0.0004**	-0.0022*	-0.0008
	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0002)	(0.0012)	(0.0005)
Business profits	0.0087	0.0085	0.0059	0.0005	0.0135**	0.0009	0.0033	0.0094
	(0.0067)	(0.0067)	(0.0041)	(0.0034)	(0.0066)	(0.0128)	(0.0613)	(0.0286)
ln(applied amount)	0.0129*	0.0129*	0.0129**	0.0151**		0.0290**	0.1371*	-0.0233**
	(0.0072)	(0.0072)	(0.0052)	(0.0063)		(0.0134)	(0.0700)	(0.0105)
ln(applied maturity)	-0.0020	-0.0018	-0.0051	0.0142**		0.0339**	-0.0723	-0.0085
	(0.0101)	(0.0101)	(0.0081)	(0.0062)		(0.0163)	(0.1272)	(0.0081)
Interest rate					0.7229***			
					(0.2302)			
ln(approved amount)					0.0136			
					(0.0095)			
ln(adjusted maturity)					0.0347***			
					(0.0132)			
Approved share					-0.0833***			
					(0.0253)			
Personal guarantee					0.0211			
					(0.0149)			
Mortgage collateral					-0.0308**			
					(0.0139)			
Chattel collateral					0.0206			
					(0.0229)			
Wald test (for male borrowers)								
Male & Female loan officer versus								
Male & Male loan officer		-0.0514***	-0.0219	-0.0522***	-0.0467***	-0.0635**	-0.2184**	-0.1059***
p-value		0.0052	0.1589	0.0030	0.0072	0.0228	0.0445	0.0004
Observations	6,775	6,775	6,670	14,003	6,775	4,273	6,771	7,772
Country	Albania	Albania	Albania	Albania	Albania	Albania	Albania	Bolivia
Regression model	Probit	Probit	Probit	Probit	Probit	Probit	Hazard	Probit
Sample	First&last	First&last	First&last	All first	First&last	First&last& terminated	First&last	First&last
Problem loan definition	30 days	30 days	60 days	30 days	30 days	30 days	30 days	30 days
Year, Sector*Branch, Loan destination fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
All control variables*Female	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Table IV. Arrear probability and loan officer gender – repeat loans

This table contains the marginal effects of the outcome test for repeat loans using the same set of 141 (195) loan officers that were used for the Albanian (Bolivian) borrowers in the baseline regressions in columns 2 and 8 of Table III. Probit regression models I and II use Albania data, while models III and IV are based on Bolivian data. Models I and III use samples of repeat and at the same time last loans, while models II and IV use all repeat loans. The dependent variable is the occurrence of a borrower being in arrears for more than 30 days at least once over the whole lifetime of her loan (1 if arrears > 30 days, 0 otherwise). The independent variables are as in Table IIIplus three additional variables capturing the borrower loan history of with the bank: *Duration relationship* provides the number of years since the first loan application of the borrower, *Any previous application rejected* is a dummy variable indicating any previous rejection of a loan application (1 = rejection), *Any previous loan in arrears > 30 days* is a dummy variable indicating any previous loan in arrears for more than 30 days (1 = if arrears > 30). Note that the variable *Any previous application rejected* is not available in columns 3 and 4 because rejected loan applications are not available for Bolivia. Results for the additional control variables and the interaction terms are omitted. The combination *Female & Male loan officer* serves as the reference group. A Wald test is used to analyze the null hypothesis that the difference between *Male & Female loan officer* and *Male & Male loan officer* equals zero. Standard errors are clustered at the loan officer level and are reported in parentheses.*,**,*** indicate significance at the 10, 5, and 1 percent level, respectively.

	Regression model			
Independent variable	I	II	III	IV
Female & Female loan officer	-0.0077**	-0.0092**	-0.0236***	-0.0187**
	(0.0025)	(0.0035)	(0.0076)	(0.0078)
Male & Female loan officer	0.0285	0.0422	-0.0176	-0.0340
	(0.0645)	(0.0457)	(0.0551)	(0.0384)
Male & Male loan officer	0.0330	0.0603	0.0052	-0.0134
	(0.0663)	(0.0587)	(0.0677)	(0.0461)
Duration relationship	-0.0028***	-0.0049***	-0.0615***	-0.0428***
	(0.0009)	(0.0009)	(0.0084)	(0.0068)
Any previous application rejected	0.0129***	0.0173***		
	(0.0050)	(0.0042)		
Any previous loan in arrears > 30 days	0.1671***	0.2161***	0.1545***	0.1672***
	(0.0427)	(0.0307)	(0.0323)	(0.0283)
Wald test (for male borrowers)				
Male & Female loan officer versus	-0.0045	-0.0181***	-0.0228***	-0.0206***
Male & Male loan officer	0.1682	0.0097	0.0060	0.0043
p-value				
Observations	6,375	12,538	8,061	14,017
Country	Albania	Albania	Bolivia	Bolivia
Sample	Repeat&last	All repeat	Repeat&last	All repeat
Socio-demographic control variables	Yes	No	Yes	No
Full set of further baseline control variables	Yes	Yes	Yes	Yes
Year, Sector*Branch, Loan destination fixed effects	Yes	Yes	Yes	Yes
All control variables*Female	Yes	Yes	Yes	Yes

Table V. Alternative performance measures and loan officer gender

This table contains Tobit regression results for the baseline samples of borrowers from Albania (models I and II) and Bolivia (III and IV). The dependent variable is the ratio of realized payments over scheduled payments. We use two different versions of this variable: *Rec1* equals the *Sum of capital repayments* / *Approved loan amount*, *Rec2* is calculated as (*Sum of capital & interest (re)payments*) / (*Approved loan amount & Sum of scheduled interest payments*). *Rec1* and *Rec2* are both truncated at 1. The sample sizes are slightly reduced because of data availability for these alternative performance measures. All control variables and interaction terms are as in Table III and are omitted from the table. The combination *Female & Male loan officer* serves as the reference group. A Wald test is used to analyze the null hypothesis that the difference between *Male & Female loan officer* and *Male & Male loan officer* equals zero. Standard errors are clustered at the loan officer level and are reported in parentheses. *,**,*** indicate significance at the 10, 5, and 1 percent level, respectively.

	Performance measure			
Independent variable	Rec1	Rec2	Rec1	Rec2
Female & Female loan officer	0.2504***	0.2172***	0.3273***	0.2734***
	(0.0834)	(0.0716)	(0.0668)	(0.0583)
Male & Female loan officer	0.0754	-0.0214	0.5250*	0.4267*
	(0.9250)	(0.8028)	(0.3117)	(0.2555)
Male & Male loan officer	-0.0229	-0.1187	0.1679	0.1296
	(0.9171)	(0.7964)	(0.3050)	(0.2497)
Wald test (for male borrowers)				
Male & Female loan officer versus				
Male & Male loan officer	0.0983**	0.0973**	0.3571***	0.2971***
p-value	0.0428	0.0274	< 0.0001	< 0.0001
Observations	6,773	6,773	7,750	7,750
Country	Albania	Albania	Bolivia	Bolivia
Sample	First&last	First&last	First&last	First&last
Full set of baseline control variables	Yes	Yes	Yes	Yes
Year, Sector*Branch, Loan destination fixed effects	Yes	Yes	Yes	Yes
All control variables*Female	Yes	Yes	Yes	Yes

Table VI. Test for differences in screening for Albanian borrowers

This table contains the marginal effects for a test whether female and male loan officers experience screening differences for Albanian borrowers. The Probit regression models are based on different sub samples of loan applications: model I is based on 8,187 loan applications that are at the same time first and last applications per borrower; model II uses 15,857 first loan applications; model III employs 7,590 loan applications that are at the same time repeat and last applications per borrower; model IV is based on 14,763 repeat loan applications. The dependent variable is the approval decision (1 for an approved loan, 0 otherwise). The combination *Female & Male loan officer* serves as the reference group. A Wald test is used to analyze the null hypothesis that the difference between *Male & Female loan officer* and *Male & Male loan officer* equals zero. Standard errors are clustered at the loan officer level and are reported in parentheses. *,**,*** indicate significance at the 10, 5, and 1 percent level, respectively.

	Regression model			
Independent variable	I	II	III	IV
Female & Female loan officer	0.0109	0.0033	-0.0103	-0.0059
	(0.0126)	(0.0101)	(0.0162)	(0.0129)
Male & Female loan officer	0.0229	0.0222	-0.0107	0.0629
	(0.0888)	(0.0441)	(0.0997)	(0.0572)
Male & Male loan officer	0.0079	0.0151	0.0034	0.0705
	(0.0893)	(0.0422)	(0.0920)	(0.0467)
Wald test (for male borrowers)				
Male & Female loan officer versus				
Male & Male loan officer	0.0150	0.0071	-0.0141*	-0.0076**
p-value	0.1961	0.3700	0.0983	0.0320
Observations	8,187	15,827	7,590	14,763
Country	Albania	Albania	Albania	Albania
Sample	First&last	All first	Repeat&last	All repeat
Socio-demographic control variables	Yes	No	Yes	No
Full set of further baseline control variables	Yes	Yes	Yes	Yes
Loan history & duration control variables	No	No	Yes	Yes
Year, Sector*Branch, Loan destination fixed effects	Yes	Yes	Yes	Yes
All control variables*Female	Yes	Yes	Yes	Yes

Table VII. Test for differences in workload of female and male loan officers

This table contains the results of a test for differences in the workload of female and male loan officers. We measure the workload in terms of the handled approved loans (columns 1 to 4) and loan applications (columns 5 to 8) by male respectively female loan officers in different time intervals. For example, male loan officers handled 19.0 loan applications in their first year at the Albanian bank whereas female loan officers processed 18.4 loan applications, on average. The comparison is based on all loans in the sample, regardless of whether any information for the control variables used in the other analyses was available or not. Panel A provides results for Albanian borrowers. We restrict the analysis to the 141 loan officers included in the baseline regression of column 2 in Table III. Panel B provides results for Bolivian approved loans. We restrict the analysis to the 195 loan officers included in the baseline regression of column 6 in Table III. Note that the maximum number of years a loan officer worked for the Bolivian lender is capped at three years because our data starts in 2004. Loan application data is not available for Bolivia. One-sided p-values are provided for a standard t-test for differences between the workloads.

Panel A: Albania

Time a loan officer works for the bank	Average number of approved loans			One-sided	Average number of loan applications			One-sided
	Male loan officer	Female loan officer	Difference	p-value	Male loan officer	Female loan officer	Difference	p-value
Up to 1 year	14.8	13.8	1.0	0.362	19.0	18.4	0.6	0.447
Up to 2 years	59.0	52.2	6.8	0.253	71.9	71.1	0.8	0.475
Up to 3 years	122.4	117.3	5.2	0.401	148.5	155.6	-7.1	0.617
Up to 4 years	195.0	172.4	22.6	0.221	242.8	230.0	12.9	0.347
Up to 5 years	226.1	197.6	28.5	0.197	288.6	269.2	19.5	0.303
Up to 6 years	228.1	205.6	22.4	0.258	292.8	283.1	9.7	0.402
Maximum	228.1	207.8	20.2	0.281	292.8	286.2	6.6	0.435

Panel B: Bolivia

Time a loan officer works for the bank	Average number of approved loans			One-sided
	Male loan officer	Female loan officer	Difference	p-value
Up to 1 year	16.9	23.8	-6.9	0.062
Up to 2 years	86.5	101.5	-15.0	0.156
Up to 3 years	224.1	240.6	-16.5	0.295

Table VIII. Arrear probability and loan officer gender – interaction with experience

This table contains the marginal effects of the outcome test with the gender of borrowers and loan officers together with interactions with loan officer experience. Probit model I is based on the 6,775 baseline loans from Albania, corresponding to the baseline regression of column 2 in Table III, while model II uses the 7,772 baseline loans from Bolivia (column 8 of Table III). The dependent variable is the occurrence of a borrower being in arrears for more than 30 days at least once over the whole lifetime of her loan (1 if arrears > 30 days, 0 otherwise). In addition to the independent variables of Table III, we interact the borrower/loan officer gender pairs with the loan officer's experience that is approximated by the number of loan applications handled by the respective loan officer until a certain loan was granted. The combination *Female & Male loan officer*Loan applications per loan officer* serves as the reference group. The first Wald test is used to analyze the null hypothesis that the difference between *Male & Female loan officer* and *Male & Male loan officer* equals zero. The second Wald test is used to test the null hypothesis that the difference between *Male & Female loan officer*Loan applications per loan officer* and *Male & Male loan officer*Loan applications per loan officer* equals zero. Standard errors are clustered at the loan officer level and are reported in parentheses. *,**,*** indicate significance at the 10, 5, and 1 percent level, respectively.

	Regression model	
Independent variable	I	II
Female & Female loan officer	-0.0522**	-0.1242***
	(0.0187)	(0.0351)
Male & Female loan officer	0.2297	-0.2473*
	(0.3032)	(0.1133)
Male & Male loan officer	0.2649	-0.1970
	(0.3542)	(0.1370)
Female & Female loan officer*Loan applications per loan officer	0.0250	-0.0562
	(0.0872)	(0.0916)
Male & Female loan officer*Loan applications per loan officer	-0.0684	-0.1952**
	(0.0908)	(0.0974)
Male & Male loan officer*Loan applications per loan officer	0.1110	0.0451
	(0.0812)	(0.0445)
Loan applications per loan officer	-0.0207	0.0734
	(0.0733)	(0.0731)
Wald tests (for male borrowers)		
Male & Female loan officer versus		
Male & Male loan officer	-0.0352	-0.0503*
p-value	0.6235	0.0726
Male & Female loan officer*Loan applications per loan officer versus		
Male & Male loan officer*Loan applications per loan officer	-0.1794***	-0.2403***
p-value	0.0008	0.0094
Observations	6,775	7,772
Country	Albania	Bolivia
Sample	First&last	First&last
Full set of baseline control variables	Yes	Yes
Year, Sector*Branch, Loan destination fixed effects	Yes	Yes
All control variables*Female	Yes	Yes

Table IX. Legal status and loan officer gender for Albanian borrowers

This table contains the marginal effects for a test whether the loan officers monitor differently with respect to the legal status of the borrower using the Albanian dataset. The first three columns show the results of Probit regressions for three subsamples of loans granted to legal entities. The first column contains the results for first and at the same time last loans to legal entities, the second column for all first and the third column for all loans to legal entities. Columns 4-6 show results of Probit regressions for the same subsamples of loans for natural entities. The dependent variable is the occurrence of a borrower being in arrears for more than 30 days during the lifetime of her loan (1 if arrears > 30 days, 0 otherwise). Since we cannot observe the gender of the legal entities, we cannot use our borrower-loan officer gender combinations, but rather only use the dummy indicating the loan officer gender (and the borrower gender for columns 4 to 6). Standard errors are clustered at the loan officer level and are reported in parentheses. *,**,*** indicate significance at the 10, 5, and 1 percent level, respectively.

	Legal entities			Natural entities		
Independent variable	First & last	All first	All	First & last	All first	All
Female loan officer	0.0032	0.0166	0.0016	-0.0456***	-0.0291***	-0.0208***
	(0.0121)	(0.0164)	(0.0138)	(0.0152)	(0.0103)	(0.0066)
Female				-0.1631	-0.1169	-0.0885**
				(0.1023)	(0.0562)	(0.0286)
Observations	213	452	1,209	6,775	14,003	26,541
Country	Albania	Albania	Albania	Albania	Albania	Albania
Socio-demographic control variables	No	No	No	Yes	Yes	Yes
Full set of further baseline control variables	Yes	Yes	Yes	Yes	Yes	Yes
Year, Sector*Branch, Loan destination fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
All control variables*Female	No	No	No	Yes	Yes	Yes

Appendix AI. Sample characteristics for Bolivian borrowers

This table contains borrower, loan, and loan officer characteristics for 7,772 approved loans from the Bolivian lender used in the baseline analysis. The table includes the first and last loan for each borrower. We further drop loans with unreasonable entries for the borrower's age (smaller than 18 or larger than 75 years), missing gender information for borrower and loan officer, and unreasonable entries for applied loan size (smaller than 100 or larger than 100,000 USD). The first column provides the means for all loans, while column 2 (3) provides the means for female (male) loan officers only. *Arrear* is a dummy variable indicating whether a borrower was in arrears for more than 30 days at least once over the whole lifetime of the loan, *Female* is a dummy variable indicating the gender of the borrower (female = 1), *Female loan officer* is a dummy variable indicating the gender of the loan officer (female = 1), *Loan applications per loan officer* is a loan officer experience proxy indicating the number of loan applications handled by the loan officer until the respective loan was granted, divided by 1,000, *Age of loan officer* is the age of the loan officer at the time the loan was granted measured in years, *Age of borrower* is the age of the borrower at the time of the loan application, *Civil status* is a dummy variable indicating whether the borrower is married (married = 1), *Wage earner* is a dummy variable indicating whether the borrower is self-employed or at least partly an employed wage earner (wage earner = 1), *Number persons household* indicates how many persons including the borrower are in the household of the borrower, and *Borrower lives in La Paz* is a dummy variable indicating whether the borrower lives in or outside La Paz (in La Paz = 1). *Leverage* (total liabilities over total assets), *Cash over assets*, *Total assets* (in USD), and *Business profits* (monthly, in USD) are taken from the borrowers' financial statements. *Applied amount* is the loan size applied for by the borrower in US dollars while *Applied maturity* is the loan maturity in days the borrower applied for. Results for the lender's bank branches, the loan destinations, and the borrowers' business sectors are omitted from the table to save space. The phone availability proxy is also omitted because all borrowers had a phone in the sample period.

	Mean | Loan officer gender						
Variable	All	Female	Male	SD	5%	Median	95%
Arrear (30 days)	0.304	0.236	0.361	0.460			
Female borrower	0.508	0.499	0.515	0.500			
Loan officer characteristics							
Female loan officer	0.454	1.000	0.000	0.498			
Loan applications per loan officer	0.384	0.363	0.402	0.299	0.025	0.340	0.936
Age of loan officer	30	29	31	4	24	29	39
Borrower characteristics							
Age of borrower	38	39	37	11	23	36	59
Civil status	0.396	0.404	0.389	0.489			
Wage earner	0.046	0.049	0.044	0.210			
Number persons household	2.396	2.339	2.443	1.463	1.000	2.000	5.000
Borrower lives in La Paz	0.635	0.735	0.552	0.481			
Business characteristics							
Leverage	0.005	0.005	0.005	0.045	0.000	0.000	0.000
Cash over assets	0.249	0.275	0.228	0.333	0.004	0.090	1.000
Total assets	6.578	7.333	5.950	19.062	0.089	1.520	26.795
Business profits	0.150	0.162	0.140	0.402	-0.109	0.135	0.595
Loan characteristics							
Applied amount	1,355	1,384	1,331	2,832	124	600	4,999
Applied maturity	192	170	210	306	30	30	720